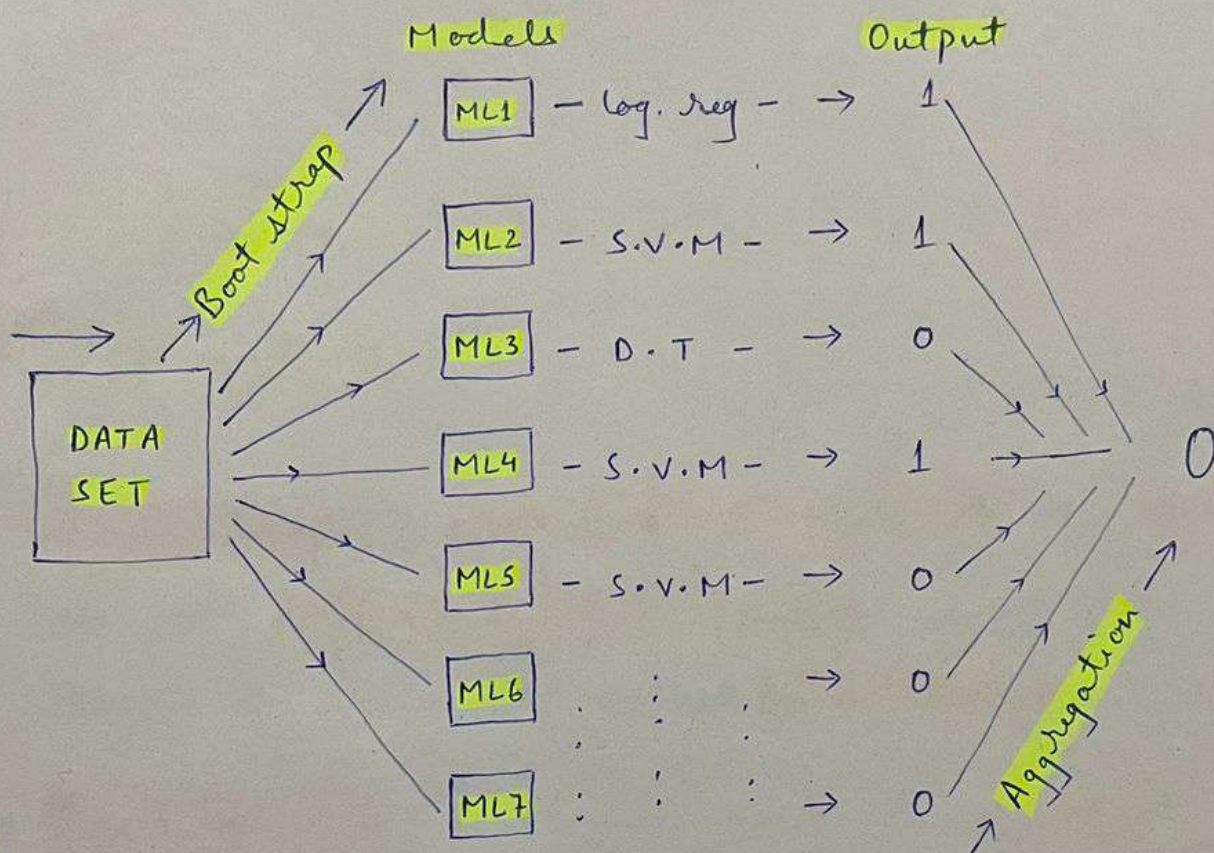


Random Forest

Bagging:



Consider we have dataset of classification problem and we perform set of operations using different algo (Algorithm) parallelly to get corresponding output.

Once we have the output after operations from n different models we decide final output based on the majority voted classifier means what max of Algo has predicted. For above dataset output is 0 predicted by 4 Algo & 1 predicted by 3. Thus final output is 0.

Above concept of combining output of multiple parallel individual models to predict final output is called Bagging of Algorithm.

Two words comes in play during Bagging :

— Bootstrap.

— Aggregation.

- **Bootstrap**: Dividing of dataset to pass on to different ML Models using different Algo to train is called Bootstrap.
- **Aggregation**: Once we have the output from different trained model generated after Bootstrap. Process of merging those output to get most occurred final output is called Aggregation.

Technique of Bootstrap and Aggregation is called Ensemble technique.

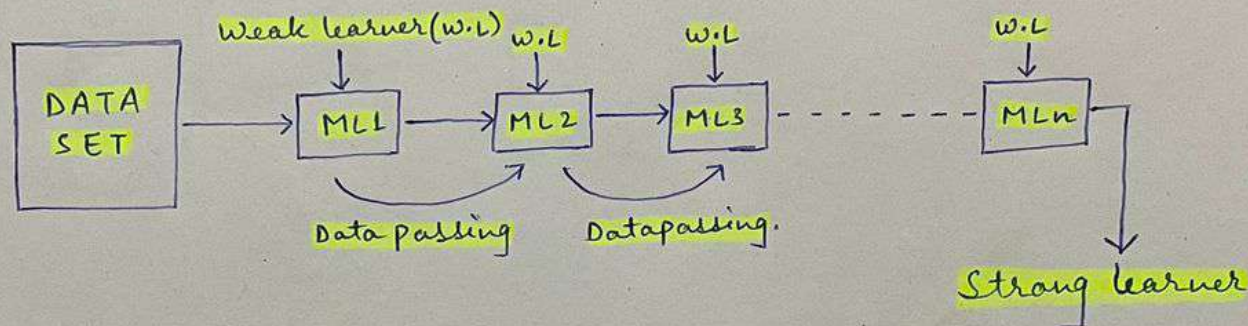
Random forest classifier:

when we choose final Aggregated output based on Major voting classifier means choosing the one having max. no. of output as final output.

Random forest regression:

when we choose final Aggregated output based on Average or Mean of the output of Bootstrapped individual Algorithm.

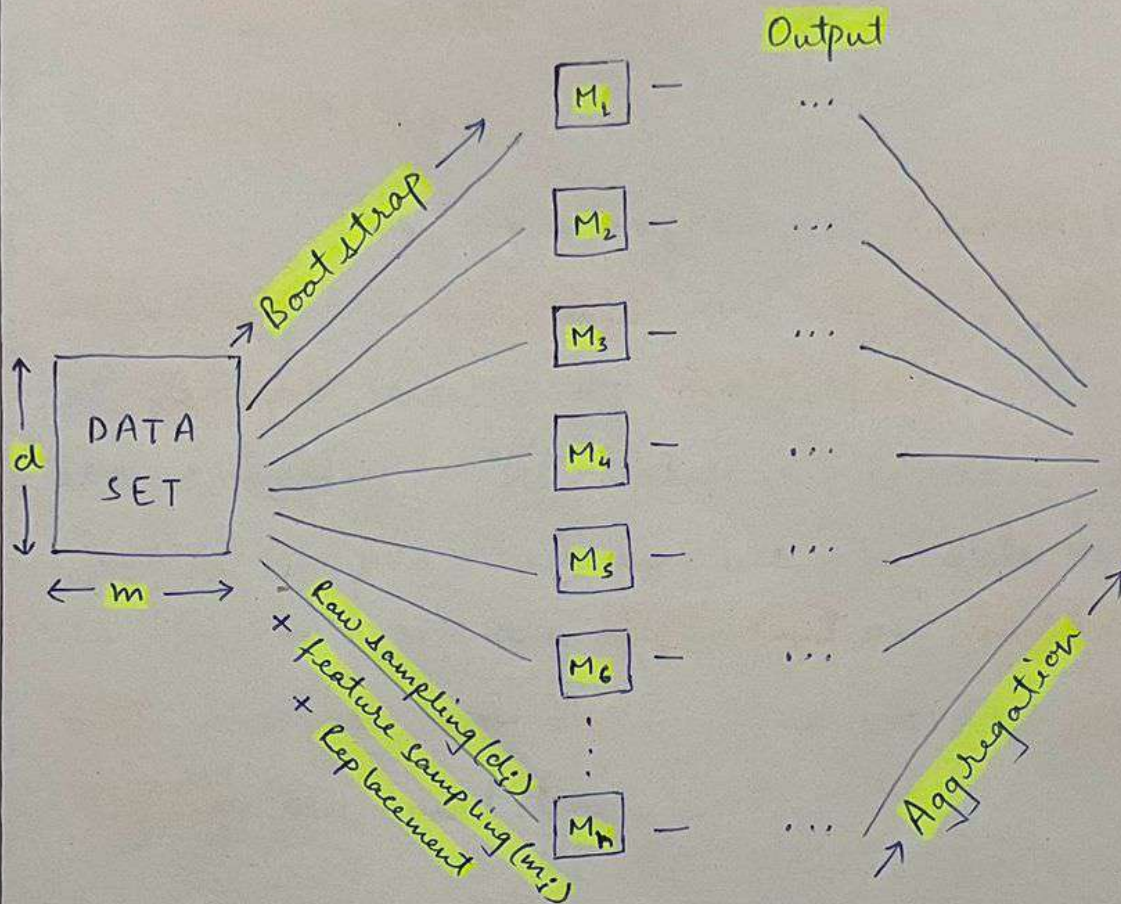
Boosting:



When we apply M.L algo on the dataset which passes through weak learner it continues to pass the data to going forward weak learner for which the Algo is not performing well. For datas for which W.L are performing well will give the output.

All the M.L Algo's are connected sequentially which was earlier parallelly in case of Bagging.

Random forest classification / Regression:



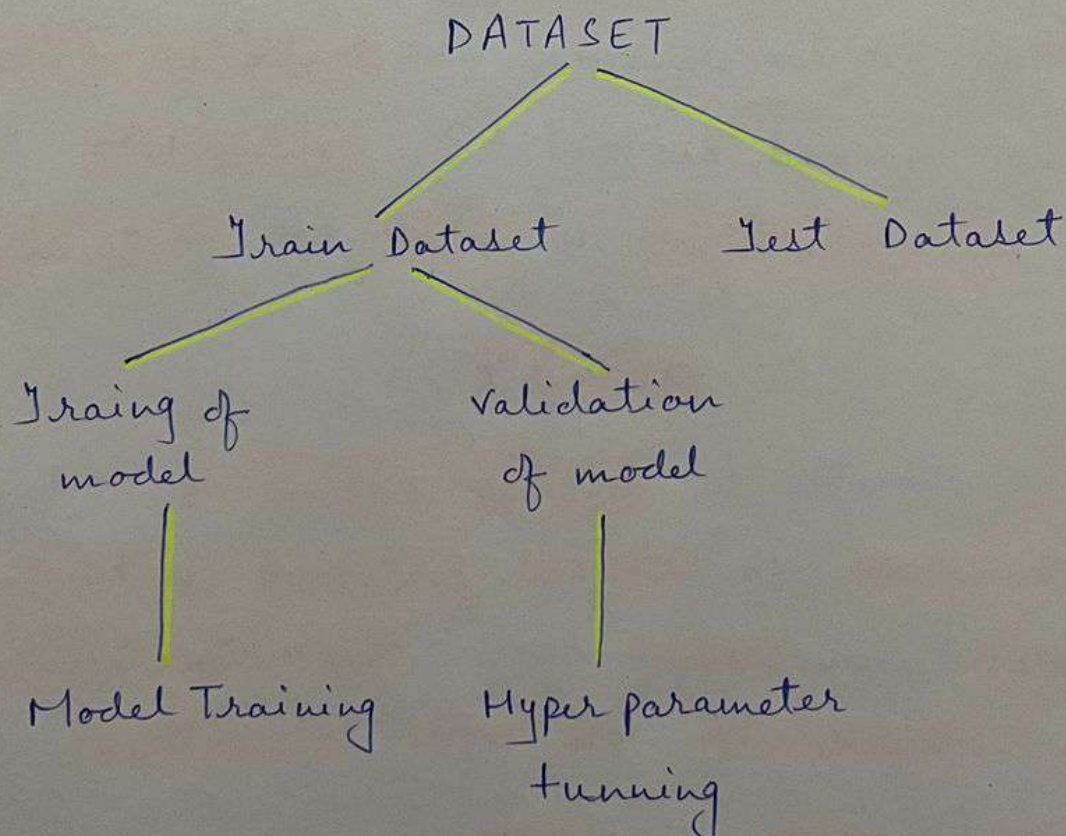
Consider parent data set d which will be passed to further ML models with different Algo $M_1, M_2, M_3, \dots, M_n$ with dataset splitted as $d_1, d_2, d_3, \dots, d_n$ and feature sampling splitted as $m_1, m_2, m_3, \dots, m_n$.

There is possibility of same datapoints being available in different M.L Algo means same data in $(d_1 \rightarrow d_2 \rightarrow d_n)$ few data points may collide.

when we draw **Individual Decision Tree** on **huge dataset**, there is maximum chance of **overfitting**.

Thus by using above **technique** of **splitting** the **datasets** and **applying Algo** over it **reduces** chance of **overfitting**. Thus we are reducing High variance in case of overfitting to low variance. we are able to do so because we are **dependent** on **multiple D.T** rather than **one**. Thus we are **generalizing** the model.

Out of Bag Evaluation:



Oob-Score :

When we do prediction of the validation data, let's the accuracy comes 85%.

Then, Validation error

$$= 1 - .85$$

$$= .15$$

0.15 is validation error and is also called Oob-Score error.

Validation error means what % of data out of whole data is untouched means not being selected in consideration in any of M.L Algo. It happens because we are selecting the data on random basis.

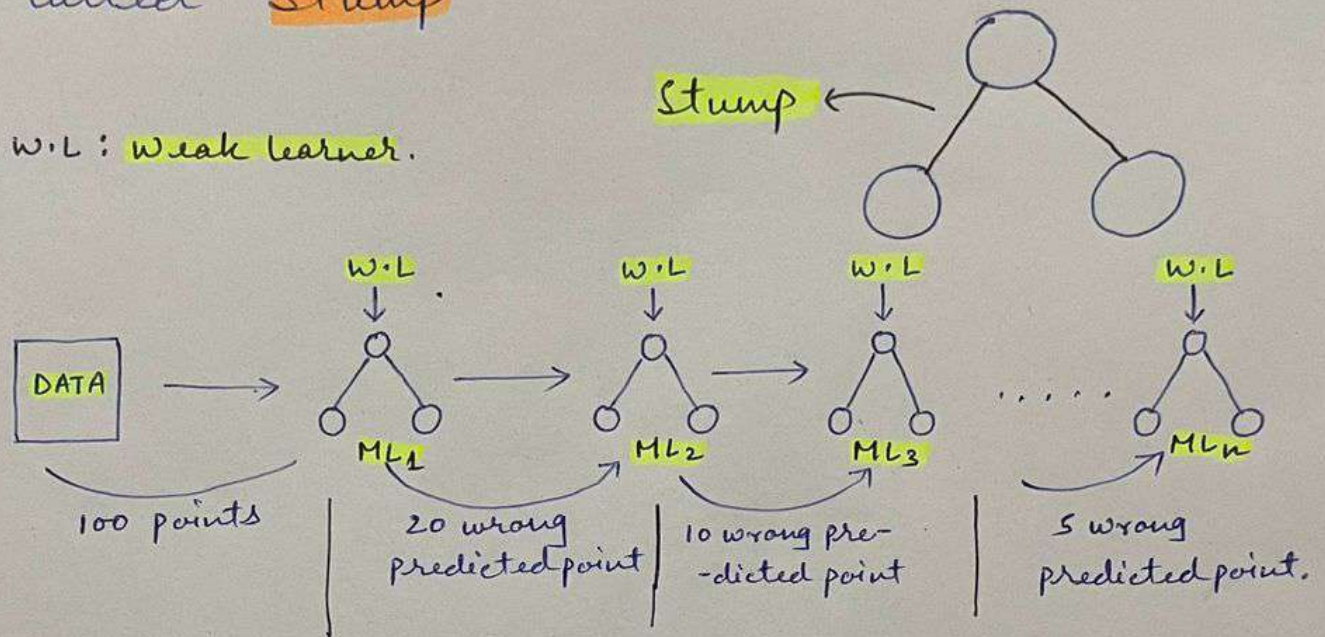
Ada Boost.

It's Ensemble method as stands for Adaptive Boosting. weights are assigned to each instances, with higher weight assigned to incorrectly classified instances.

when we choose depth of D.T as 1, so less depth led to Under fitting.

Decision Tree (D.T) with just **depth = 1** is called **Stump**

W.L : **Weak learner**.



Suppose **initially** we have **100 datapoints**. Being passed to Model (ML₁) it predict **right result** for **80 points** & **wrong** for **20**. Then **only wrong** one will be **passed to further Models** [weak learners] and **same will continue** till we get **right prediction** for all points.

Final function;

$$= f = \alpha_1 (ML_1) + \alpha_2 (ML_2) + \alpha_3 (ML_3) + \dots + \alpha_n (ML_n)$$

α : weight

ML_i : weak learner